**Commodity Price Pass-Through in Differentiated Retail Food Markets**

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**Abstract:**

Price for nearly all basic commodity rose at unprecedented rates throughout early 2008, only to fall nearly as fast as financial markets and global economies began to collapse. Rising food prices in 2008 led to concerns that commodity price spikes would lead to more general food inflation, but by early 2009 interest focused more on the seeming inability of food prices to fall back down with commodity prices. This study provides an empirical investigation into the pass-through of commodity prices to retail prices for two different types of food products: potatoes and fluid milk. The results show that pass-through depends on the nature of the food in question, but is generally consistent with theoretical models of pricing by sellers of multiple, differentiated products. In particular, pass-through rates tend to be lower for processed (differentiated) products during periods of falling input prices than when input prices are rising. For less processed products, pass-through tends to be higher during regimes of both rising and falling input prices. Our results show that pass-through depends on the degree of pricing power possessed by all channel members and, more generally, suggest a nuanced approach to understanding retail food price inflation.

**keywords:** commodity prices, conduct, industrial organization, inflation, market power, nested logit, pass-through, random parameters model.

**JEL Codes:** C35, D12, D43, L13, L41, Q13.

## Introduction

During the past two years, policymakers have taken notable concern of the impact of commodity price fluctuations on the well-being of U.S. households in general, and particularly those facing financial hardship (Dessus, Herrera, and de Hoyos, 2008). Indeed, prices for important production inputs such as wheat, corn, oats, rice, and potatoes increased by 51, 56, 37, 72, and 30 percent respectively from June 2007 to June 2008 (Farmdoc) so there was a general concern that food price inflation would follow accordingly. Although the world financial crisis that arose in late 2008 promised even greater hardship for the newly unemployed and underemployed, the subsequent economic slowdown also brought the hope of lower food prices as commodity prices began retreating to more normal levels. For example, by June 2009 wheat, corn, oat, rice, and potato prices fell 25, 26, 30, 13, and 12 percent respectively from their June 2008 levels (Farmdoc). However, analysts in the business media and government agencies observed that supermarket prices were declining at a much slower rate than those of production input prices, raising concerns that market intermediaries were taking advantage of the situation and profiting from price volatility and consumer uncertainty (Boyle, 2009). Whether their observations constitute evidence of market power or the normal fluctuations of prices in a complex vertical channel, however, is an unresolved empirical question. Consequently, the goal of this research is to better understand the phenomena of price pass-through in the food marketing channel and how it is influenced by vertical strategic interaction between manufacturers and retailers.

Heterogeneity in production, marketing and distribution systems means that it is generally not possible to draw sweeping conclusions regarding the pass-through of commodity prices to retail prices of all foods. Nonetheless, theory provides some general concepts that guide our understanding and our expectations regarding how rates of wholesale-retail price pass through should behave when input prices are changing. First, the level of concentration and subsequent market power exertion by any channel members has a direct effect on theoretical rates of price pass-through. Bulow and Pfleiderer (1983) show, for example, that input price changes are passed along the channel at the rate of 100% for perfectly competitive sellers, and 50% for monopolist sellers. On the other hand, buying power by powerful monopsonist manufacturers or retailers results in cost reductions via their potential to refuse input price increases (Hamilton and Sunding 1997). Empirical research by Martinez (2008) and Volpe and Lavoie (2008) provide supporting evidence for this latter form of market concentration by showing that the growth of supercenters (who arguably exercise significant buying power with upstream suppliers) has reduced retail food prices in many markets.

Second, the degree to which wholesalers pass input price changes on to retailers depends on the substitutability of inputs required to manufacture a particular food product (Gardner, 1975). In other words, more inputs required to produce an end product, the least likely it is for a price increase in a small number of these inputs to have a notable effect on the price of the final good. This notion was central to the arguments of Leibtag (2008) who suggested that, regardless of skyrocketing commodity prices, consumer food prices would likely adjust only a little because food commodities only constitute a portion of their production process. However, while this argument may hold for heavily processed foods such as ready to eat cereal or frozen entrees, it is less likely to apply to minimally processed foods such as fresh fruits and vegetables.

Third, increases in input prices tend to be passed along to end consumers much quicker than price reductions. Market power exertion is often cited as the culprit of such asymmetric price transmission. However, several studies highlight institutional mechanisms that could account for such behavior. For example, Richards and Patterson (2005) show that price rigidity could be the result of market uncertainty and the fixed costs associated with changing shelf prices. Alternatively, collusive agreements between channel members could result in trigger-price strategies that are consistent with pass-through asymmetries (Rotemberg and Saloner, 1986; Lewis, 2004).

In this study, we estimate the relationship between commodity price inflation and retail food prices, while testing hypotheses regarding the nature of competition within the food marketing channel. In doing so, we contribute to the literature on price pass-through by accounting for structural attributes of the food marketing channel that are likely to affect the role of commodity price inflation in determining prices at the supermarket. First, we allow for vertical strategic interaction between manufacturers and the downstream retail market where competition involves portfolios of both national brands and private label products. This approach is consistent with other structural marketing studies that highlight the need to control for the proper mode of competition between channel members (Sudhir, 2001; Kim and Cotterill, 2008). Second, to highlight the possible differences between pass-through-rates for products that differ by degree of manufacturer processing, we apply our model of manufacturer-retailer pricing to two commonly purchased food products – potatoes, and fluid milk. Finally, we contribute methodologically by estimating the first model of manufacturer/retailer pricing that includes both a structural model of the vertical distribution channel and a model of asymmetric price adjustment.

Our findings provide evidence that commodity-inflation pass-through depends critically on the product market in question as the nature of the vertical channel for potatoes differs significantly from that of fluid milk. Specifically, for potatoes we find that both retailers and manufacturers narrow margins during periods of commodity price inflation and expand margins when commodity prices fall. This finding is consistent with sellers taking advantage of short-term profits made available by consumers who still maintain high price expectations. This outcome may also be the result of more basic competitive forces. For example, Hamilton (2009) shows that in markets involving multiple differentiated products that Bertrand-Nash competition can cause overshifting any increases in input prices. For milk, we find that retailers and manufacturers narrow margins when input prices rise as well as when they fall. Because retail markets for milk are more competitive than for potatoes, retailers are reluctant to lose market share by raising milk prices when pressures to do so arise. Without higher retail prices, retailers cannot pay higher wholesale prices so both sides of the vertical channel are forced to reduce their margins. When input prices are falling, the relative competitiveness of retail markets again dominates – retailers reduce their prices in order to gain market share, reducing the derived demand for milk at the wholesale level.

The remainder of the paper is organized as follows. We first present a brief overview of theoretical models of cost pass-through to retail prices. As part of this section we highlight our expectation that the structure of the product market will play a critical role in determining the impact of input price inflation on retail prices. Next, we outline a structural model of retail pricing consisting of a discrete choice model of demand and a two-stage retailer/manufacturer price optimization framework on the supply side. In the third section we describe our potato and milk data and draw attention to the differences between the two product categories in terms of pricing dynamics and processing intensity. The fourth section contains our explanation of the estimation and identification of our model. Empirical results as well as the implications of our findings are presented in the fifth section, while a final section provides conclusions and suggestions for future research.

**Economic Model of Input Price Pass-Through**

The rate of cost pass-through depends on the structure of the market. Gardner (1975) shows that the degree to which downstream prices respond to upstream cost changes depends on the elasticities of supply and demand for the farm and non-farm inputs, but he assumes competition throughout. In a more general model, Bulow and Pfeiderer (1983) show that the retail price change in response to a change in upstream cost should be equal to the change in cost, multiplied by a ratio of the demand curve slope to the slope of the marginal revenue curve. Similarly, but in a more complete model of the marketing channel, Holloway (1991) extends the Gardner (1975) model to include deviations from competitive pricing of farm commodities, and finds pass-through rates generally less than 50%.[1] Their analyses, however, do not consider differentiated product markets.

While much of the previous research is cast in terms of undifferentiated commodity markets, Sudhir (2001) presents a theoretical and empirical analysis of cost pass-through in a highly differentiated environment – the U.S. automobile industry. His findings are consistent

[1] Holloway (1991) estimates the elasticity of the retail-farm price ratio with respect to marketing input costs. This can be interpreted as analogous, but not identical to, our definition of a pass-through rate.

with predictions from theoretical research, namely that the pass-through rate will be higher in perfect competition or in Bertrand-Nash pricing games than in monopoly or Cournot competition. Similarly, Moorthy (2005) provides a theoretical analysis of price setting by competing, multiple-differentiated-product retailers and demonstrates the importance of strategic complementarity in setting prices. Kim and Cotterill (2008) find a similar result in a context closer to the one considered here: the U.S. processed cheese market. More recently, Hamilton (2009) addresses the joint effect of pricing and variety selection among multi-product retailers in leading to pass-through rates that may exceed 100%. Although the data for this study do not describe sales by individual retailers, we account for this effect by including demand relationships among a wide variety of potentially complementary products.

Models of tax incidence in public economics arrive at an analogous conclusion with respect to *ad valorem* or unit taxes – that the pass-through rate of *ad valorem* taxes can be higher in more competitive pricing environments than less (Anderson, de Palma and Kreider, 2001; Delipalla and Keen, 1992) depending upon the price-reaction of rival firms.[2] Froeb, Taschantz and Werden (2005), however, demonstrate that it is not necessarily the elasticity of demand that determines the pass-through rate, but rather the curvature of demand. They use this insight to explain why some mergers result in large price increases absent synergies, and yet pass any cost reductions through at a relatively high rate. Consequently, the empirical model developed in this paper is as flexible as possible, with the curvature determined by the interaction between consumer heterogeneity and product attributes (Berry, Levinsohn and Pakes, 1995; Nevo, 2001).

[2] Anderson, de Palma and Kreider (2001) arrive at the somewhat surprising result that overshifting an *ad valorem* or unit tax under Bertrand-Nash competition in differentiated products will occur just as in a homogeneous Cournot oligopoly such as in Delipalla and Keen (1992).

Moreover, we allow for the possibility that conduct, as measured by the deviation from competitive behavior, may indeed be endogenous to changes in upstream cost as rising prices may provide either manufacturers or retailers a “smokescreen” to increase their margins.

## Empirical Model of Pass-Through in Differentiated Product Markets

### *Overview*

In this section, we describe the structural model used to estimate the pass-through rate of farm prices to retail prices for two fundamentally different food categories, one minimally processed and one involving relatively more processing: fresh potatoes and milk. These categories are selected because they represent different levels of value-added from the base food commodity and, as such, should be impacted to differing degrees by commodity price inflation. In each case, the econometric model is based on a two-stage game theoretic framework of the food supply chain. Namely, suppliers are assumed to behave as Stackelberg leaders in a two-stage pricing game in which suppliers pose the terms of supply contracts to retailers, who then accept or reject all terms of the contract depending on the incentives provided (Sudhir, 2001 and Villas-Boas and Zhao, 2005, and others). In the second-stage of the game, retailers who accept the contracts set retail prices and consumer demand follows. As is common in empirical models of vertical strategic interaction, we solve and estimate the game backward, beginning by estimating consumer demand, solving the retailer problem and then estimating the suppliers’ problem conditional on retail demand elasticities and pricing conduct.

Within this traditional structural industrial organization framework, we estimate the impact of commodity price inflation on retail pass-through, retail margins, supplier margins and, hence, market power at both levels, by introducing "conduct parameters" into the retail and supplier models (Draganska and Klapper, 2007; Richards, Hamilton and Patterson, 2009; Richards and Hamilton, 2006). Unlike models of conjectural variations, the conduct parameters in this model are atheoretic, meaning that they do not represent any postulate over retailer or manufacturer behavior, but rather measure the degree of departure of the industry from completely competitive or Bertrand outcomes. By allowing these conduct parameters to vary with both time and the level of input prices, the interaction effect allow us to determine the impact of input price changes not only on marginal cost, but pass-through and market power.

*Consumer Demand*

Consumer demand is represented by a random utility model in which consumers are assumed to make a discrete choice of one product (brand or variety) from among those represented in our retail data sample, or some other product from another outlet, which is defined as the outside option. The utility consumer $i$ obtains from consuming product $j$ during week $t$ is a function of the product's price ($p_{jt}$), product-specific preferences, $\gamma_{ijt}$, and a set of product attributes ($x_{jk}$):

$$u_{ijt} = \gamma_{ij} + \alpha_i p_{jt} + \sum_{k=1}^{K} \beta_k x_{jkt} + \xi_{jt} + \varepsilon_{ijt}, \qquad \textbf{(1)}$$

where the product attributes include a binary discount variable ($d_j$) that assumes a value of 1 if the product is reduced in price by at least 10% from one week to the next, and then returned to its previous value in the following week, an interaction term between the discount and price ($d_j p_j$)

and a time trend, $t$, $\xi_{jt}$ is an error term that accounts for all product-specific variation in demand that is unobserved to the researcher such as the perceived quality, the amount of shelf-space allocated to it, or unmeasured advertising, and $\varepsilon_{ijt}$ is an i.i.d. type I extreme value error term that accounts for consumer-specific heterogeneity in preferences. With this error assumption, the utility specification in (1) implies a logit discrete choice demand model.

Because consumers can buy either potatoes or milk from sources other than those captured by our scanner data, we extend the simple logit model to consider the hierarchical nature of a consumer's choice process: consumers first choose whether to buy from the traditional supermarkets described by our data, or another source, and then the specific brand or variety.[3] Consequently, we modify the distributional assumption governing $\varepsilon_{ijt}$ by allowing it to follow instead a Generalized Extreme Value (GEV, McFadden, 1978) distribution. With the GEV assumption, we allow for differing degrees of substitution among products within each group: supermarket purchases and others. In terms of the utility model introduced in (1), the GEV extension involves including a composed error such that:

$$u_{ijt} = \gamma_{ij} + \alpha_i p_{jt} + \sum_{k=1}^{K} \beta_k x_{jkt} + \xi_{jt} + \tau_{ijt} + (1 - \sigma_J)\varepsilon_{ijt}, \qquad \textbf{(2)}$$

where $\tau_{ijt}$ is an error-component (Cardell, 1997) that makes the entire term: $\tau_{ijt} + (1 - \sigma_J)\varepsilon_{ijt}$ extreme-value distributed as well. The aggregate probability that consumer $i$ purchases product $j$ in group $J$, or the market share, is given by the product of the conditional probability of buying

[3] Scanner data typically includes only supermarkets with \$2.0 million + in sales, and excludes stores that do not participate in national data syndication efforts: Wal-Mart, Costco, and Target notable among them.

within a particular group and the probability of the group as a whole, or:

$$s_j = s_{j|J} s_J = \frac{e^{(\delta_j + \varphi_i)/(1-\sigma_J)}}{D_J^{\sigma_J}[\sum_J D_J^{(1-\sigma_J)}]}, \tag{3}$$

where $\delta_j$ is the mean utility of product $j$, or the part of utility that does not vary over consumers, and $\varphi_i$ is the part that does, $s_{j|J}$ is the share of product $j$ among all supermarket sales, $s_J$ is the share of group $J$ in overall volume sales, and $D_J = \sum_{j \in J} e^{(\delta_j + \varphi_i)/(1-\sigma_J)}$ represents the inclusive value from purchasing from group $J$ so that $s_J = D_J^{1-\sigma_J} / \sum_J D_J^{1-\sigma_J}$. Faced with a total market size of $M$, therefore, the quantity sold of product $j$ is written as: $Q_{jt} = s_{jt} M$.

As is well known, however, the GEV model still suffers from the independence of irrelevant alternatives (IIA) property within groups, which means that the substitution elasticities between products depends only on their market shares and not on more fundamental attributes that are likely to influence demand. Consequently, we allow the product-preference and marginal utility of income parameters in (3) to vary over consumers in a random way (Berry, Levinsohn and Pakes, 1995; Nevo, 2001; McFadden and Train, 2000). Specifically, the marginal utility of income (also referred to as the price-response parameter) is normally distributed over consumers so that:

$$\alpha_i = \alpha_0 + \sum_{l=1}^{L} \alpha_l z_{il} + \sigma_\alpha \nu_i, \quad \nu_i \sim N(0,1), \tag{4}$$

where $\alpha_0$ is the mean price response across all consumers, $\alpha_l$ is the effect of attribute *l* on price sensitivity, $z_i$ is vector of individual attributes and $\nu_i$ is the random, consumer-specific variation in response with parameter $\sigma_\alpha$. Similar to Erdem (1996) and Nair, Dube, and Chintagunta (2005), we also assume that product-specific preferences depend on the attributes of each individual:

$$\gamma_{ij} = \gamma_{0j} + \sum_{l=1}^{L} \gamma_l z_{il} + \sigma_\gamma \mu_i, \quad \mu_i \sim N(0,1), \tag{5}$$

where $\gamma_{0j}$ is the mean preference for product *j*, $\gamma_l$ is a vector of individual attribute effects, and $\mu_i$ is the random, consumer-specific effect on product preferences. In contrast to the IIA property of a simple logit model, the heterogeneity assumption in (4) creates a general pattern of substitution over alternatives *j* through the unobserved, random part of the utility function given in (1). Non-IIA substitution is critical in models of differentiated product pricing because inferences regarding either upstream or downstream market power would otherwise be entirely confounded by mis-estimates of the partial elasticity of demand facing each product.

With a discrete choice model of demand, it is assumed that each consumer purchases only one unit of the chosen product. Because our data measures aggregate market shares, therefore, we aggregate over the distribution of consumer heterogeneity to arrive at an expression for the share of each product variety of the entire market. Because the random-parameters logit model introduces a large number of parameters relative to the simple logit model, we follow Nevo (2001), among others, and write the indirect utility function in terms of two sets of variables – those that are assumed to be random and those that are not:

$$u_{ijt} = \delta_{jt}(p_{jt}, x_j, z_l, \xi_{jt}; \gamma, \alpha, \beta, \sigma_J) + \varphi_{ijt}(p_{jt}, \nu_i, \mu_i; \sigma_\alpha, \sigma_\beta) + \varepsilon_{ijt}, \tag{6}$$

where $\delta_{jt}$ is the mean level of utility that varies over products, but not consumers, and $\varphi_{ijt}$ is the idiosyncratic part that varies by consumer and product. Define the densities of $\mu_i$ and $\nu_i$ as $f(\mu)$ and $g(\nu)$, respectively, so that the market share of product $j$, obtained by integrating over the distributions reflecting consumer heterogeneity, becomes:

$$s_{jt} = \int\int \frac{e^{(\delta_{jt} + \varphi_{ijt})/(1-\sigma_J)}}{D_J^{\sigma_J}(\sum_J D_J^{1-\sigma_J})} f(\mu) g(\nu) \, d\mu \, d\nu, \tag{7}$$

which can then be estimated in aggregate data using simulated maximum likelihood (SML) algorithms (Train, 2003). Simulation methods are required to estimate the demand-side model because there is no closed form-expression for market share as in the simple logit case (Berry, 1994). It is this expression for aggregate demand, therefore, that channel members consider in forming their pricing decisions.

*Retail and Wholesale Pricing Model*

Given the aggregate nature of our data, we characterize the marketing channel as consisting of a single, multi-product retailer, and multiple, single-product suppliers.[3] Although there are clearly many retailers, and multi-product suppliers in reality, we gain nothing by modeling this structure,

[3] This "monopoly retailer" model is common in the empirical industrial organization literature (Slade, 1995; Villas-Boas and Zhao, 2005) and, although not strictly true in most markets is a near approximation given the survey data reported in Slade (1995) that supports a model in which shoppers choose a single outlet for their groceries. Individual stores are thus appropriately characterized as local monopolies.

because our focus is on market power relationships between the retail sector and consumers downstream, and the retailer and suppliers upstream. Consistent with prior evidence on the vertical structure of food-product markets, the retailer behaves as a Stackelberg follower: suppliers specify a wholesale price given their expectations of how the retailer will respond, and the retailer then sets prices paid by consumers (Kadiyali, Vilcassim, and Chintagunta, 1996, 1999). We solve for the sub-game perfect Nash equilibrium in the usual way: by working backward from the retailer to the supplier's problem.

Beginning with the retailer decision, and suppressing the time period index ($t$) for clarity, the retailer sets a price for each product, $p_j$, each week to solve the following problem:

$$\Pi^r = \max_{p_j} M \sum_{j=1}^{J} (p_j - r_j - w_j) s_j, \qquad \textbf{(8)}$$

where $M$ is total market demand, $w_j$ is the wholesale price, $r_j$ are unit retailing costs, and $s_j$ is the market share defined above.[4] Retailing costs are assumed to be constant, which is plausible given the share of store-sales accounted for by any individual product. Under the manufacturer-Stackelberg assumption, the retailer sets prices taking wholesale prices as given.

We assume the retailer sets prices as a local monopolist selling a differentiated-product and thus internalizes all intra-store pricing externalities (behaves as a perfect category manager). Consequently, the retailer's first-order condition for product $j$ is given by:

[4] We refer to the wholesale price throughout as the price paid by the retailer, which differs from the grower price by packing costs, shipping costs and any other contractual terms specified by the wholesaler.

$$s_j + \sum_{k=1}^{J} \frac{\partial s_k}{\partial p_j}(p_k - r_k - w_k) = 0, \quad j = 1,2,...,J, \tag{9}$$

for all $J$ products in the store. Stacking the first-order conditions for all products and solving for retail prices in matrix notation gives:

$$\boldsymbol{p} = \boldsymbol{r} + \boldsymbol{w} - \boldsymbol{S}_p^{-1}\boldsymbol{S}, \tag{10}$$

where $\boldsymbol{p}$ is an $J$ x 1 vector of prices, $\boldsymbol{w}$ is a $J$ x 1 vector of wholesale prices, $\boldsymbol{r}$ is a $J$ x 1 vector of product-specific retailing input prices, $\boldsymbol{S}$ is an $J$ x 1 vector of market shares, and $\boldsymbol{S}_p$ is a $J$ x $J$ matrix of share-derivatives with respect to all retail prices. Because the suppliers take the retailer's optimal response into account in setting upstream prices, equation (10) represents the retail decision rule that frames their pricing decisions.

Each supplier is assumed to set wholesale prices in order to maximize the surplus over production costs for the particular brand or variety he or she sells, conditional on the retailer's response. Again assuming individual wholesalers sell all products sold by the retailer, we index the supplier model over individual products, $j$, and write supplier profit as:

$$\Pi_j^m = \max_{w_j} M(w_j - c_j)s_j, \tag{11}$$

where $c_j$ is the (constant) production cost of product $j$ incurred by the supplier and the other variables are as described above. The first-order condition for the supplier is taken with respect to the wholesale price and is written:

$$s_j + \sum_{k=1}^{J} \frac{\partial s_k}{\partial p_l}\frac{\partial p_l}{\partial w_j}(w_k - c_k) = 0, \quad j = 1,2,...,J, \tag{12}$$

which is simply an expression of the supplier's vertical pricing problem, taking the retailer's best reply into account and recognizing that the supplier has to take into account the effect of his own price changes on the retail price of all other products. As in Sudhir (2001) and Villas-Boas and Zhao (2005), we derive expressions for the wholesale price derivatives by totally differentiating the retail first-order conditions to find:

$$\sum_{k=1}^{J} \frac{\partial s_j}{\partial p_k}\frac{\partial p_k}{\partial w_j} + \sum_{k=1}^{J}\sum_{l=1}^{J}(p_l - r_l - w_l)\left(\frac{\partial^2 s_l}{\partial p_j \partial p_k}\right)\frac{\partial p_k}{\partial w_j} + \sum_{l=1}^{J}\frac{\partial s_l}{\partial p_j}\frac{\partial p_l}{\partial w_j} = \frac{\partial s_j}{\partial p_j} \quad \forall \ j = 1,2,\ldots J, \tag{13}$$

which can be simplified by defining a $J$ x $J$ matrix $\boldsymbol{G}$ with typical element $g_{jk}$ such that:

$$g_{j,k} = \frac{\partial s_j}{\partial p_k} + \sum_{l=1}^{J}(p_l - r_l - w_l)\left(\frac{\partial^2 s_l}{\partial p_j \partial p_k}\right) + \frac{\partial s_k}{\partial p_j}. \tag{14}$$

Using this expression to write the wholesale margin and stacking over all suppliers, the margin is written as:

$$\boldsymbol{w} - \boldsymbol{c} = -((\boldsymbol{G}^{-1}\boldsymbol{S_p})\boldsymbol{S_p} * \boldsymbol{I_N})^{-1}\boldsymbol{S}, \tag{15}$$

where $\boldsymbol{I}_N$ is a $J$ x $J$ identity matrix and * indicates element-by-element multiplication. Wholesaling costs are unobservable, however, so we substitute the wholesale margin in (15) into the retail margin equation (10) to arrive at a single-equation expression for the total retail-cost margin:

$$\boldsymbol{p} = \boldsymbol{r} + \boldsymbol{c} - \boldsymbol{S}_{\boldsymbol{p}}^{-1}\boldsymbol{S} - ((\boldsymbol{G}^{-1}\boldsymbol{S}_{p})\boldsymbol{S}_{\boldsymbol{p}} * \boldsymbol{I}_{N})^{-1}\boldsymbol{S}, \tag{16}$$

which allows the estimation of pass-through rates, both from retailing and wholesaling costs to retail prices and, perhaps more importantly, from farm prices to retail prices.

To this point, all of parameters required to identify the equilibrium margins are contained in the demand side estimates ($\boldsymbol{S}_p$ and $\boldsymbol{G}$) and from the estimated marginal cost functions.[5] Marginal retailing and wholesaling costs, in turn, are estimated as linear functions of input prices, $\boldsymbol{v}_r$ and $\boldsymbol{v}_w$ such that: $\boldsymbol{r}(\boldsymbol{v}_r) = \eta_{r0} + \sum_{i=1}^{I} \eta_{ri} v_{ri}$, and $c_j(\boldsymbol{v}_w) = \eta_{w0} + \eta_{w1} b_j + \sum_{l=1}^{L} \eta_{wl} v_{wl}$ for retailing and wholesaling costs, respectively, where $b_j$ is the farm-price received from wholesalers at the grower level. Wholesaling costs are assumed to be separable between agricultural (farm purchases of potatoes) and non-agricultural inputs (Gardner, 1975). These functions are estimated after substituting the demand parameters into (16) in the two-step procedure described below. Because wholesale prices are unobservable, however, we need a method of estimating the effect of commodity price changes, through wholesale prices, to retail prices.

*Estimating Farm-Retail Pass-Through Rates*

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[5] Detailed derivations of each matrix are available from the authors, but are similar to Villas-Boas and Zhao (2005) and Berto Villas-Boas (2007). Note that these parameters are also interpreted as measuring the extent of deviation from the maintained Bertrand-Nash assumption.

In the empirical pass-through rate literature (Kim and Cotterill, 2008; Besanko, Dube, and Gupta, 2005) it is typically assumed that pass-through is instantaneous as the empirical models are inherently static. However, many others provide evidence of asymmetric price adjustment, so the weight of the empirical research suggests otherwise (Borenstein, Cameron and Gilbert, 1997, for example).[6] There are essentially two ways of accounting for dynamic behavior of pass-through rates: (1) an atheoretic, time-series approach that focuses on the dynamic time series properties of the relationship between wholesale and retail prices, and (2) structural models that investigate the rate at which retail-wholesale price relationships return to some maintained equilibrium. Because we believe vertical relationships in the food industry are characterized by somewhat complicated non-competitive equilibria, to not take the nature of the game into account in explaining price adjustment would be a fundamental misspecification of the market. However, many theoretical models do not adequately account for the rich dynamics involved. Consequently, we provide a synthesis of these approaches and test for asymmetry in retail adjustment to changes in wholesale prices within the context of a theoretically-consistent model of vertical supply relationships.

In retail food markets, the implicit assumption is that both the retailer and suppliers optimize according to the structure of the game and, as such, there is no deviation from the theoretical equilibrium. To explain price dynamics in food markets, we allow for deviation from the monopoly / Nash equilibrium to occur for two reasons: (1) market power relationships among retailers or suppliers that differ from the game described above, and (2) asymmetric price adjustment that can arise for any of the reasons cited by Lewis (2004), namely consumer search,

[6] See Frey and Manera (2007) for an excellent, recent review of the literature from both agricultural and non-agricultural markets.

volatility, or market power itself.

As Villas-Boas and Zhao (2005) and Draganska and Klapper (2007) suggest, observed margins may differ from those expected under the maintained monopoly / Nash pricing model. While errors in optimization are always a possibility, there may also be structural reasons for deviations from the theoretical equilibrium. Market power, either more or less than expected, contractual relationships or more subtle forms of strategic behavior are all possibilities. Another possibility is that generalized commodity price inflation creates an environment of price uncertainty that allows retailers and / or wholesalers to temporarily raise margins. In order to test hypotheses regarding the fundamental causes of asymmetrical pass-through, we focus on the effects of price inflation, or the rates of change in commodity prices, on pass-through rates from the farm to wholesale level and from wholesale to retail.

We allow for deviations from the hypothesized profit maximizing choices by the retailer and the Bertrand-Nash behavior by the wholesalers by introducing parameters in (16) that measure the deviation of the retail margin (**φ**) and supplier margin (**θ**) from the maintained assumption at each level:

$$\boldsymbol{p} = \boldsymbol{c} + \boldsymbol{r} - ((1/\varphi)\boldsymbol{S}_{\boldsymbol{p}})^{-1}\boldsymbol{S} - \theta((\boldsymbol{G}^{-1}\boldsymbol{S}_{\boldsymbol{p}})\boldsymbol{S}_{\boldsymbol{p}} * \boldsymbol{I}_{\boldsymbol{N}})^{-1}\boldsymbol{S}, \qquad \textbf{(17)}$$

where both φ and θ are functions of exogenous variables that are thought to influence each player's ability to earn positive margins, namely upward and downward movements in key input prices.

Retailers claim that food manufacturers use environments in which commodity (input) prices are rising to increase their margins (Boyle, 2009). At the same time, food manufacturers argue that contractual obligations, inventory accounting and other rigidities prevent them from changing prices with every fluctuation in the commodity market and, moreover, that retailers are not passing through wholesale price changes to the consumer. Consequently, the influence of retailer and wholesaler markup behavior on retail prices when commodity prices are changing is an unresolved empirical issue.

Early econometric models of asymmetric price adjustment considered current downstream prices as functions of upward and downward movements in upstream prices (Tweeten and Quance, 1968) or cumulative price movements (Houck, 1977; Ward, 1982; Kinnucan and Forker, 1987). More recently, however, others have recognized that asymmetrical price adjustments must take into account the econometric implications of a long-run equilibrium between two price series.[7] Namely, if both price series are non-stationary and integrated of order 1, then there may exist a long run relationship between the variables expressed in first differences. Importantly, any conclusions formed regarding asymmetric price adjustment in levels could very well be in error because the underlying relationship between the two variables may indeed be spurious. Granger and Newbold (1974) were the first to recognize the importance of considering whether or not two time series are cointegrated, while Granger and Lee (1989) develop the error correction model (ECM) to deal with this problem in a consistent way.[8] Despite the fact that the ECM approach has become very popular, there is some question as to whether, over a relatively short, high-frequency time series of retail and wholesale potato and milk prices, the price series are indeed cointegrated.

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[7] Frey and Manera (2007) provide a detailed and exhaustive review of the empirical literature on this issue.

[8] Others have extended this ECM approach to account for the possibility that underlying pressures to change retail prices must overcome an unobserved threshold value before eliciting a response in the shelf price. Such threshold cointegration models (Azzam, 1999; Goodwin and Piggott, 2001; Abdulai, 2002) represent a valuable contribution to the literature given the observation that retail prices are indeed costly to adjust.

In our application, it is not likely that either series, constrained by production costs and low-cost imports, will exhibit a drift without bound over the sample period. Nonetheless, we conduct a series of unit root tests (Phillips-Perron) prior to specifying the final version of the price-adjustment model. We find that we reject the null hypothesis of a unit root for both retail and wholesale price series, for each panel member in both datasets. Consequently, we specify the econometric price-adjustment model without adjusting for error correction, but in a manner that is still able to test for asymmetry in the adjustment of retail prices to changes in grower prices.

In order to test our hypotheses regarding the fundamental causes of asymmetrical cost pass-through, we provide for two avenues of adjustment asymmetry: directly from farm prices to retail prices, and through retailers' and wholesalers' markup behavior. Without a theoretical basis to guide a choice of functional form for the deviation parameters, we write both as linear functions of a constant term as well as upward and downward changes in commodity prices: $\pi_{j,\tau}^{U} = dw_{j,t-\tau}\delta^{+}$ and $\pi_{j,\tau}^{D} = dw_{j,t-\tau}\delta^{-}$ where $dw_{j,t-\tau}$ is the change in wholesale prices from period $t - \tau$ to period $t$, $\delta^{+} = 1$ when prices rise and $\delta^{-} = 1$ when they fall. Therefore, we write both deviation parameters as functions of the upward and downward movement in wholesale prices:[9]

$$\varphi_j = \varphi_0 + \varphi_1\pi_j^{U} + \varphi_2\pi_j^{D}, \qquad \textbf{(18)}$$

and:

$$\theta_j = \theta_0 + \theta_1\pi_j^{U} + \theta_2\pi_j^{D}. \qquad \textbf{(19)}$$

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[9] Conceptually, the deviation parameter can vary by product *j* because commodity-price inflation is product-specific. However, to avoid a proliferation of parameters in the empirical model, we restrict the deviation parameters to be equal.

In this way, we test whether retailers or wholesalers, respectively, face greater competitive pressures in an inflationary environment, as argued by Lewis (2004), or regard inflationary periods as an opportunity to exploit buyers' confusion over what the true price should be, as suggested by Benabou and Gertler (1996).

The deviation parameters are interpreted as measuring the extent of deviation from the maintained pricing game by either the retailer ($\varphi$) or the wholesalers ($\theta$) (Villas-Boas and Zhao, 2005; Draganska and Klapper, 2007). In the case of the retailer, the maintained hypothesis is monopoly pricing, so an estimated value of $\varphi$ above 1.0 suggests that the retailer prices higher than the monopoly level. Conversely, if $\varphi < 1.0$, then the retailer prices less than a perfect monopoly would. Upstream, the maintained hypothesis is that wholesalers price as Bertrand-Nash competitors with respect to each other. In this case, a value of $\theta > 1.0$ indicates greater-than-Bertrand pricing and $\theta < 1.0$ suggests pricing that is more competitive than Bertrand. In the extreme, if $\theta = 0$, then wholesalers do not take advantage of the differentiated nature of their products and price as purely competitive commodity sellers. We have no priors on the values of these parameters in relation to either the maintained or competitive benchmarks given that there are structural arguments supporting either competitive or non-competitive pricing by either the retailer or the set of wholesalers.

Commodity price inflation has an asymmetric effect on retail prices if we reject the null hypothesis that $\varphi_1 = \varphi_2$. In this study, however, our concern lies more in the sign of each parameter than whether they differ. Specifically, if $\varphi_1 > 0$, then retail margins widen during periods of commodity-price inflation. In other words, the retailer prices less competitively as a result of commodity price inflation, possibly because an environment of rising prices provides the retailer with the ability to exploit consumers' expectations that prices should be higher. In a regime of falling commodity prices, $\varphi_2 < 0$ implies that retail margins widen as commodity prices fall (the value of the margin is larger if commodity prices are falling). Assuming wholesale prices fall with commodity prices, retailers are not reducing their prices as a competitive, frictionless equilibrium would suggest.[10] Researchers typically interpret this result as indirect evidence of retailer market power (Lewis, 2004; Frey and Manera, 2007). Alternatively, if $\varphi_2 > 0$, then retail margins narrow as commodity prices fall – evidence that retailers are either willing to reduce profits in order to maintain market share and are, indeed, highly competitive, or that wholesalers do not pass reductions in their costs through to the retail level by reducing wholesale prices in a timely manner. Further, if both retail adjustment parameters are positive and $\varphi_1 > \varphi_2$ then retail margins widen more completely when farm prices are rising than margins narrow when farm prices are falling.

The interpretation is similar on the manufacturer side, but the margin is defined as the difference between total production cost (the farm price plus packing and distribution costs for minimally processed items) and the wholesale price paid by retailers. First, if $\theta_1 < 0$ then wholesale margins fall as commodity prices rise – a situation in which wholesalers cannot pass on higher farm prices to retailers. On the other hand, if $\theta_1 > 0$, then wholesale margins rise with commodity prices, which is only possible if suppliers are able to obtain a pass-through rate of greater than 100%. When commodity prices are falling, $\theta_2 < 0$ implies that wholesale margins rise. This is precisely the situation retailers are arguing exists in the current environment (spring

[10] Note that this interpretation assumes that the "menu cost" of price adjustment at retail are either not a significant factor in preventing retailers from reducing shelf prices in response to wholesale price changes, or are captured by the direct effect captured in the marginal retailing cost function.

2009), where manufacturers are holding wholesale prices at levels justifiable during the commodity price spike of 2008 despite the fact that farm prices are now dramatically lower. Although this could be due to contractual obligations, inventory purchases, hedging activities or other internal pricing methods, it does appear to be a *prima facie* case of wholesaler market power. Conversely, if $\theta_2 > 0$, then wholesale margins fall when commodity prices are falling. This is to be expected if the wholesale sector is competitive and suppliers begin to undercut each other in an attempt to gain market share. We test for each of these possible outcomes using the retail and wholesale data described in the next section.

*Pass-Through Simulation*

The conduct parameters described in the previous section measure only the direct effect of farm price changes on each margin, but not the indirect effects through product substitution. Therefore, we calculate the implied pass-through rate from commodity prices for each product to its retail price by introducing shocks to the commodity price and calculating the resulting change in retail prices (Kim and Cotterill, 2008). Expressing the response of retail prices in proportionate terms provides an estimate of the theoretical pass-through rate. In each case, we simulate pass-through under the estimated game structure, and one that is more and one that is less competitive. The resulting pass-through rates suggest whether we can evaluate the impact of imperfect competition on price dynamics in minimally-processed food markets.

Specifically, define the pass-through rate between farm and retail prices as: $\Delta_{RF}$. To show how this value is calculated, re-write the retail margin equation to explicitly include the arguments of each cost function and simplify the markup notation so that:

$$\boldsymbol{p} - \boldsymbol{c}(\boldsymbol{v}_w, \boldsymbol{b}) - \boldsymbol{r}(\boldsymbol{v}_r) + \boldsymbol{m}_r(\boldsymbol{p};\varphi) + \boldsymbol{m}_w(\boldsymbol{p}, \boldsymbol{v}_r;\theta) = 0, \tag{20}$$

where $\boldsymbol{m}_r$ is the retail markup and $\boldsymbol{m}_w$ is the wholesale markup and $\boldsymbol{b}$ is the farm-price of the commodity. Notice from (20) that the retail price vector appears both on its own and as a component of the wholesale and retail mark-up equations. Therefore, we allow the farm price to vary by a fixed amount (+ / - 10%), and then solve (20) implicitly for the price vector. With this solution, we then calculate the percentage change in retail prices that results from the change in cost. Using equation (20), we then calculate the pass-through for product $j$ as:

$$\Delta_{RF}^{j} = \frac{p_j^1 - p_j^0}{(c_j^1(v_{jw}, b^1) - m_{jr}^1 - m_{jw}^1) - (c_j^0(v_{jw}, b^0) - m_{jr}^0 - m_{jw}^0)}, \tag{21}$$

where the 1 superscript refers to the price and cost terms observed following the change in input prices, and the 0 superscript is the base scenario. Written this way, the pass-through rate is interpreted in percentage terms and shows the proportion of each cost change that is passed through to retail prices. Values greater than 1.0 (100%) mean that retailers raise prices by more than the increase in cost, and values less than 1.0 suggest that retailers absorb some of every cost increase, perhaps to avoid losing market share.

**Data Description**

The potato data consist of 143 weeks (week of January 8, 2006 through week of September 28, 2008) of market-level retail scanner data from five markets: Atlanta, Chicago, Dallas, Los Angeles and New York. The data consist of dollar sales, unit volume (pounds), promotion activity and attribute indicators for ten potato varieties (fingerling, Idaho, purple, red, red creamer, russet, white, yellow, organic, other). These data are from Fresh Look Marketing, Inc., Chicago, Illinois. Farm price data are from the United Potato Growers of America (UPGA) for each variety and represent weekly FOB price data at the packing-house door. Therefore, farm prices and wholesale potato prices, which are unobserved in the above model, are not the same and are likely to differ significantly depending on transportation costs, packing costs and other wholesale services.

Retail input prices consist of average weekly earnings of workers in the supermarket industry, weekly retail management earnings and market-specific indices of commercial electricity prices. Wholesale input prices include an index of interest, taxes and insurance costs, a measure of fuel prices (diesel fuel) and an index of business service costs. All of these input prices are from the Bureau of Labor Statistics (BLS) and are smoothed to produce weekly series from the native monthly data. In the potato demand model, the outside option is defined as the entire potential market for table-potato sales. We calculate the size of the whole market on a weekly basis by multiplying the total metropolitan statistical area (MSA) population (Bureau of Census) by the USDA estimate of per capita consumption of potatoes (ERS-USDA). The difference between the inside and the outside option is then reduced to potatoes sold through convenience stores, food service outlets and retailers that do not participate in retail-scanner data syndication (Wal-Mart, Costco, and other club and super stores). Nevo (2001) and Berry, Levinsohn and Pakes (1995) follow similar strategies in creating a broad definition of the total potential market. Finally, we take random draws from the distribution of each demographic measure (household income, age, education and household size) reported by the Current Population Survey (Bureau of

Census) to capture market-specific variation in unobserved elements in the mixed logit demand model. The potato data is summarized in table 1a below.

The data used for the milk model is similar in nature to the potato data, but reflects inherent differences between data for fixed-weight consumer-packaged-goods and fresh, random-weight products. The data are again market-level retail scanner data, but represent 10 of the largest Metropolitan Statistical Areas (MSAs) in the U.S. over the 104 week period from March 4, 2007 through February 22, 2009. Therefore, both the potato and milk datasets capture the period in 2008 where commodity prices were rising rapidly, and much of the subsequent decline. We focus our analysis on the top 18 brands by local market share, as many milk brands are market-specific. Additional attributes for the milk demand model include fat content, whether the brand is organic or not, and if it is a private label. All retail input prices are the same as those defined above in the potato model (adjusted for time periods and markets), but we use an index of packaging prices instead of the interest, taxes and insurance index used in the potato model. Summary statistics for the milk data are shown in table 1b below. It is clear from tables 1a and 1b that the "natural experiment" inherent in this scanner data, namely variation in price both over time and over markets, is sufficient to identify the parameters that are the focus of our empirical analysis.

[tables 1a and 1b in here]

**Estimation Method and Identification Strategy**

For both products, we estimate the entire model in two stages. We estimate the first-stage demand model using simulated maximum likelihood (SML, Train, 2003) and the second stage using

Generalized Method of Moments (GMM, Davidson and MacKinnon, 1993). SML uses Monte Carlo simulation to solve the integral in the demand equation up to an approximation that is accurate to the number of random draws chosen, $R$. This method provides consistent parameter estimates under general error assumptions and is readily able to accommodate complex structures regarding consumer heterogeneity. In order to speed the estimation process, we simulate the multi-dimensional integral that defines the distribution of heterogeneity using $R$ draws from a Halton sequence (Train, 2003; Bhat, 2003). We find that $R = 50$ draws are sufficient to produce stable estimates without excessive estimation time. Bhat (2003) provides experimental evidence that shows Halton sequences can reduce the number of draws required to produce estimates at a given accuracy by a factor of 10. Although estimating in two stages is not maximally efficient, it does produce consistent parameter estimates at each stage. Because the second-stage GMM estimates use estimated regressors from the first, demand-stage, however, the standard errors will be inconsistent. Therefore, we estimate the model at this stage using the bootstrap estimator described by Cameron and Trivedi (2005). As a result, all inferences drawn from the supply-side model estimates will be consistent.

In aggregate, market-level scanner data, we assume retail prices are endogenous. In other words, some of the unobserved factors that are now in the econometric error term of the estimated demand equation are likely to be highly correlated with observed prices: shelf-facing, display area, in-store promotions and a host of other factors. Without an estimator that takes this into account, all parameter estimates would biased and inconsistent. Our identification strategy is well-accepted in the literature. Namely, we require instruments that are correlated with the endogenous variables, but not the unobservables in the pricing equation. Unobservable factors that are likely to influence marketing margins for the products in question include such things as targeted, market-specific advertising, chain-level merchandising efforts, or variations in local tastes that are not captured by the demographic variables included in the demand model.

Following others in this literature (Berto Villas-Boas, 2007; Draganska and Klapper, 2007) we use a variety of instruments. First, we interact retail and production input prices with the set of market binary variables. Market-specific variation in costs will be correlated with prices in the same market, but not likely to be correlated with unobservable factors in the margin equations. Second, we include a set of lagged share and margin values in order to pick up any pre-determined pricing effects. Third, we include product-specific binary variables to account for idiosyncratic supply or quality factors that are unobservable to the econometrician but are clearly important in determining either wholesale or retail margins. First-stage instrumental variables regressions show that this set of instruments explains over 90% of the variation in our endogenous price and share variables.[11] In this way, we are confident that we can identify the market conduct parameters that are key to our analysis of pass-through and market structure.

**Results and Discussion**

In this section, several sets of estimation results are of interest. We first present the demand estimates for both products in order to establish the validity of the demand model and to highlight features of each market that are likely to be relevant to retailers' and wholesalers' pass-through behavior. We then present the supply-side or pricing model estimates and tests of the central hypotheses of the paper, namely, how commodity inflation influences pricing conduct and pass-

[11] These estimation results are voluminous, but are available from the authors in a separate document.

through during periods of both rising and falling commodity prices.

Table 2 provides estimates of the random-coefficient nested-logit potato demand model. We use a number of specification tests to establish the validity of the random-parameters nested logit model. We first test whether a nested logit specification is appropriate, or whether a simpler, single-level logit model is preferred. The null hypothesis in this case is whether the nested logit scale parameter, $\sigma_J$, is statistically different from zero. A t-test of this hypothesis easily rejects the null (t-ratio = 169.968) so we conclude that a nested logit is preferred. Second, we test whether the random parameters specification is preferred to the alternative by testing whether the standard deviation of the price and intercept terms used to describe the unobserved heterogeneity in each market are statistically significant. Further, we conduct a log-likelihood ratio test in which the unrestricted version (random coefficients) is compared to a restricted version (fixed coefficients). From the results in table 2, it is clear that both of these specification tests suggest that the random coefficients version is superior, so we use this model as the basis of consumer demand and, therefore, of retail and wholesale pricing.

[table 2 in here]

A number of results from the retail potato demand model are of substantive interest for potato marketers, and to establish the validity of the demand estimates. First, the marginal utility of income (price coefficient) is negative and significant, as expected. Second, the discount effect appears to shift the demand curve, and rotate demand in a clockwise direction (at a 10% level). Both of these effects are as retailers intend. Third, the elasticity of substitution among stores is bound by 0 and 1, indicating that stores are close substitutes when preceding a potato purchase ($\sigma_J$ = 1 indicates perfect substitution). Allowing for observed heterogeneity suggests that the elasticity of demand rises (become more inelastic) in both age and education, which is expected as consumers understand the value of fresh vegetables in a healthy diet. The flexibility of the random coefficients specification is evident from the matrix of demand elasticities shown in table 3. While the own-price elasticities are less than zero, as expected, there is also considerable variation in the cross-price elasticities with most varieties.

[Table 3 here]

We expect that the demand elasticities for potatoes, which are a minimally processed (cleaned and boxed) perishable item, will differ significantly from the brand-level milk estimates. Milk undergoes pasteurization, fortification, fat-reduction and packaging prior to reaching the store, so is more highly differentiated than are potatoes. Table 4 shows the results obtained by estimating the full random coefficients model and an ordinary least squares version that does not correct for the endogeneity of retail prices.[12] Summarizing the demand estimates, we again reject the simple logit specification in favor of the nested alternative. Using the nested logit estimates, we find that price-promotion tends to shift the demand curve out during the promotion week, and rotate it in a clockwise (more inelastic) direction. As in the potato case, we again find significant variation in the cross-price elasticities across products due to the flexibility of the random coefficients approach. Relative to the potato estimates, however, the branded nature of retail milk sales means that the brand-level elasticities are much larger than the variety-level potato elasticities.

[tables 4 and 5 in here]

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[12] As in the potato case, a Hausman (1978) test is used to test the null hypothesis that all retail and wholesale prices are endogenous.

We now present the results obtained by estimating both margin models: first for potatoes and then for milk. In table 6 we present two sets of results in the case of potato margins – the second two columns assume a competitive supply sector so only allow for margin adjustment by retailers, while the first two columns allow for both competitive retailers and wholesalers. Prior to interpreting the price-adjustment parameters, however, it is first necessary to establish the validity of the GMM estimates. We do so with mis-specification tests and general tests of goodness of fit. First, with a GMM estimator, a chi-square test that compares the estimated model with a null alterative provides an indication of the overall goodness of fit of the model (Davidson and MacKinnon, 2003). From the results in table 6, based on critical chi-square values of 36.415 and 26.587 for the vertical and retail models, respectively, we reject the null hypothesis in each case that the set of parameters is jointly equal to zero. Second, we conduct a Hausman test (Hausman, 1978) of the exogeneity of retail and wholesale prices using the vertical model. With a critical chi-square value of 12.089 and a test statistic value of 44.274, we conclude that prices cannot be assumed to be exogenous, so the instrumental variables estimator is appropriate. Finally, we conduct a J-test of the overidentifying restrictions implied by the GMM estimator (Davidson and MacKinnon, 2004). The J-test is again chi-square distributed with degrees of freedom equal to the number of overidentifying restrictions. In the case of the vertical model, the GMM objective function value is 271.14, so we conclude that the set of instruments is not ideal. However, a first-stage regression of the instruments on endogenous retail prices provides an $R^2$ value of 0.943, so we argue that this set is the best available to us and that the ideal set of instrumental variables likely does not exist. Consequently, we proceed to interpret the margin-adjustment parameters using the estimated values reported in table 6.

[table 6 in here]

Our primary concern is the adjustment of retail margins to change in the farm price, and the interactions between retail and wholesale markup terms and the rate of farm price inflation. We interpret the former effect as the "direct" effect and the second as the "indirect" effect, or the impact of farm price inflation on the ability of either retailers or wholesalers to charge above-competitive margins. These results of the supply side potato model are presented in table 6. With respect to the direct effect, we find that the estimated parameter in the vertical model is positive and statistically significant from zero, indicating that the retail-cost (or total) margin rises by $0.68 per pound for every $1.00 per pound change in the price of potatoes, which implies a "partial" pass-through of 89.6%, based on the average farm price.[13] We refer to the direct effect in this table as a partial effect because the total pass-through rate must take into account the impact of cost changes on equilibrium prices, both at the wholesale and retail levels.

In terms of the indirect effect, the results in table 6 show that the fitted value of the retail conduct parameter (which includes a constant, inflationary and deflationary effect) is 0.828 while the fitted value of the wholesale conduct parameter is 0.248. This implies that potato wholesalers are nearly competitive, but retailers price nearer to the maintained monopoly level. Disaggregating pricing conduct into rising and falling input-price regimes, however, reveals more information relevant to our objectives. Recall that $\varphi_1$ refers to a regime in which commodity prices are rising, $\varphi_2$ to when they are falling, and similarly for $\theta_1$ and $\theta_2$ with respect to the wholesale mark-up term. The fact that all four parameter estimates are negative for the potato

[13] Note that the farm price does not enter into the retail margin equation because raw commodity prices in our model are not inputs to the retailer, but are to the wholesaler.

results suggests that when commodity prices are rising, both retail and wholesale margins fall. Retailers are apparently unwilling to cede market share to competitors by raising prices, so absorb some of the wholesale price increase, and require that their suppliers do so as well. On the other hand, when commodity prices are falling, the negative $\varphi_2$ estimate suggests that retail margins rise. Similar to the findings of many others in the asymmetric price-adjustment literature (Kinnucan and Forker, 1987, for example), retailers are slow to reduce their price to consumers when costs are falling in recognition of the temporary profits that are available.

Unlike other studies, however, we also find that wholesale margins rise when commodity prices are falling ($\theta_2 < 0$). This reflects the complaint voiced by retailers in the spring of 2009 following a rapid slide in commodity prices described above (Boyle, 2009). While suppliers' costs were clearly falling, they were not passing along all of their cost savings through lower wholesale prices. Our results support this allegation and, comparing the relative magnitude of the two parameters, suggest that it was rather retailers that were benefitting more than the manufacturers as the wholesale sector is considerably more competitive. While the source of suppliers' pricing power lies in branding and loyalty, the spatial market power enjoyed by retailers is evidently much stronger.

We conduct the same set of specification tests for the milk margin model, with the same qualitative results. Consequently, we again interpret the direct and indirect pass-through estimates using the vertical model. In terms of the direct effect, the pass-through parameter of 0.066 implies a pass-through rate of 3.4% at the mean farm price. With respect to the indirect effects, the fitted value of the retail conduct parameter is 0.289 and the wholesale conduct parameter is 0.542 – opposite to the potato case where wholesalers were shown to be more competitive than retailers.

The net effect on pass-through rates, however, depends on whether input prices are rising or falling. The results in table 7 show that both wholesale and retail margins narrow when input prices change in either direction. How can this be? First, consider suppliers. When input prices are rising, production costs rise relatively quickly because feed prices represent a large share of the cost of producing milk. Although suppliers appear to have more market power than retailers, milk suppliers will be unable to pass these input cost increases onto retailers if retail margins cannot widen sufficient to cover the higher wholesale prices. Further, when input prices are falling, wholesale margins do so as well. When retailers expect wholesale prices to fall, they put further pressure on suppliers to lower prices. Because manufacturers' costs are not falling as far as retailers expect (raw milk is not 100% of production costs), margins narrow. Second, on the retail side, the relatively competitive nature of retailing forces retailers to absorb some of the price increases in periods of rising prices. As a result, retailers find themselves in a cost-price squeeze as they attempt to maintain market share. However, manufacturers seem to absorb a larger portion of the rising food prices compared to retailers. Additionally, when input prices fall retailers are forced to cut prices. Moreover, retailers have greater leverage over manufacturers to lower wholesale prices because their expectation is that production costs have fallen with commodity prices. As a result, manufacturers are again forced to cede a greater share of their margin as retailers press for a decrease in the wholesale cost in order to maintain market share. In summary, neither wholesalers nor retailers benefit from inflationary or deflationary periods in the case of processed food items such as milk.

[table 7 in here]

We then simulate equilibrium changes in the retail price, wholesale price and both margins when the farm price changes by a fixed amount. By comparing the resulting pass-through rates between the estimated equilibrium and the extremes of perfect competition and collusion, we get a better sense of the effect of the competitive conduct estimated in both models on the extent to which farm price changes are translated into retail price inflation. These results are shown in table 8 below for both potatoes and milk. In general, our results agree with previous studies in that we find the rate of cost-passthrough is lower for firms with market power relative to those without, except in the case of a raw milk price increase. However, our findings differ significantly by product. While the estimated deviation from competitive behavior in potatoes implies only a slightly lower pass-through rate when commodity prices are rising, and -17.26% lower rate when commodity prices are falling, for milk the difference is 31.56% when input prices are rising and 7.01% when they are falling. This result appears to be counterintuitive, but recall that these estimates describe a net effect of retail and wholesale margin changes. For potatoes, wholesalers reduce their margins more than sufficient to offset the opposite change by retailers, so the net effect is actually a pass-through rate higher than the competitive benchmark. This is consistent with other "overshifting" results found in the public finance literature (Anderson, de Palma and Kreider, 2001). If firms set prices in a Bertrand-Nash fashion, then price complementarity in differentiated products can lead to exactly this result.

The implications of these results go beyond the two commodities studied here. If commodity-price inflation returns – as is widely expected – then policies directed at containing the impact on consumer food prices should focus not only on the cost-share of the farm input, but also the nature of the product itself. If the food in question is highly differentiated and sold through a vertical market with wholesalers and retailers, then multi-product, strategic pricing considerations will not only be important, but may dominate the argument. As is common in these situations, the efficient solution is more nuanced than the first reaction suggests.

## Conclusion and Implications

In this study, we estimate the direct and indirect pass-through of commodity price changes to the retail prices of two differentiated food products. Retail prices change directly as a result of either higher or lower wholesale prices, but indirectly as commodity inflation changes either retailers' or wholesalers' pricing power. We estimate both effects using structural models of the US potato and milk markets.

We model pass-through using a structural model of each retail food market. Demand is assumed to be discrete, which we estimate using a random parameter, nested logit model. Pricing decisions are made in a two-stage, non-cooperative game framework by wholesalers and retailers. We derive the retail pricing equations directly from the first-order conditions for multi-product retail profit maximization, and the wholesale pricing equations indirectly due to the unobservability of wholesale prices. For both retailers and wholesalers, pricing conduct is allowed to deviate from either the competitive benchmark or complete collusion through the inclusion of a conduct parameter. Pricing conduct, in turn, depends on whether commodity prices are rising or falling.

Both the potato and milk models are estimated using instrumental variables methods. We use two-years of weekly scanner data that covers the periods of rapid commodity price inflation and deflation observed during 2008 and 2009, respectively. Our results show significant differences in pass-through behavior between rising and falling commodity price regimes.

Specifically, both retail and wholesale margins in the potato market narrow when farm prices are rising, but widen when they are falling. Pass-through rates, however, are relatively high as the wholesale market is nearly competitive. These results suggest that retailers and wholesalers exercise some pricing power and perhaps exploit buyers' expectations that prices should still be high when input prices are falling.

For milk, both wholesale and retail margins narrow when commodity prices change in either direction. Because wholesalers are relatively non-competitive, pass-through rates for milk are significantly lower than in the potato example. Although wholesalers do have a degree of market power, their ability to earn higher margins is constrained by how much margin retailers are able to extract from consumers. The difference in pass-through between the milk and potato examples is primarily due to the level of perceived differentiation in the retail milk market. Whereas potatoes are typically regarded as commodities – even at the retail level – fluid milk is increasingly becoming a differentiated product through nutritional additives, packaging and brand-line extensions. Clearly, price-complementarity among differentiated products sold by Bertrand-Nash competitors creates a situation in which the usual policy prescriptions may need to be more sensitive to the nature of the product and players involved, or abandoned entirely given the inherent complexity of the relationships involved.

Future research in this area should consider the effect of commodity price inflation on equilibrium assortments offered by multi-product retailers. Hamilton (2009) shows that rising input prices should cause retailers to reduce the variety of products they offer, thus increasing the per-product demand for each, and causing further pressure on the retail price to rise. By jointly endogenizing price and variety in an equilibrium framework, we will be able to determine more accurately the path between input price changes and wholesale.

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**Table 1a. Potato Summary Data**

| Variable | N | Units | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| **Fingerling Share** | 7150 | % | 0.101 | 0.102 | 0.003 | 0.929 |
| **Idaho Share** | 7150 | % | 18.503 | 9.073 | 3.531 | 49.748 |
| **Other Share** | 7150 | % | 0.966 | 0.886 | 0.028 | 6.323 |
| **Purple Share** | 7150 | % | 0.032 | 0.033 | 0.004 | 0.225 |
| **Red Share** | 7150 | % | 13.651 | 4.817 | 6.476 | 39.576 |
| **Red Creamer Share** | 7150 | % | 2.558 | 1.628 | 0.329 | 16.584 |
| **Russet Share** | 7150 | % | 48.346 | 13.362 | 19.180 | 75.228 |
| **White Share** | 7150 | % | 8.644 | 6.404 | 0.852 | 43.813 |
| **Yellow Share** | 7150 | % | 6.159 | 3.053 | 1.444 | 17.797 |
| **Organic Share** | 7150 | % | 0.993 | 1.301 | 0.073 | 15.483 |
| **Fingerling Price** | 7150 | $ / lb. | 2.753 | 0.693 | 1.040 | 4.780 |
| **Idaho Price** | 7150 | $ / lb. | 0.629 | 0.161 | 0.330 | 1.130 |
| **Other Price** | 7150 | $ / lb. | 2.346 | 1.395 | 0.548 | 6.948 |
| **Purple Price** | 7150 | $ / lb. | 2.142 | 0.659 | 1.070 | 4.150 |
| **Red Price** | 7150 | $ / lb. | 0.811 | 0.134 | 0.450 | 1.330 |
| **Red Creamer Price** | 7150 | $ / lb. | 1.673 | 0.343 | 0.780 | 2.300 |
| **Russet Price** | 7150 | $ / lb. | 0.604 | 0.144 | 0.300 | 1.150 |
| **White Price** | 7150 | $ / lb. | 0.776 | 0.192 | 0.250 | 1.520 |
| **Yellow Price** | 7150 | $ / lb. | 0.973 | 0.195 | 0.570 | 1.460 |
| **Organic Price** | 7150 | $ / lb. | 0.981 | 0.253 | 0.331 | 1.760 |
| **Age** | 7150 | Years | 34.476 | 1.409 | 31.531 | 37.717 |
| **Education** | 7150 | Years | 10.278 | 0.330 | 9.576 | 10.868 |
| **Grocery Wages** | 7150 | $ / Week | 336.348 | 7.184 | 319.740 | 353.680 |
| **Management Wages** | 7150 | $ / Week | 771.007 | 42.879 | 695.400 | 849.780 |
| **Electricity** | 7150 | Index | 178.684 | 19.582 | 149.000 | 235.000 |
| **Interest, taxes and ins.** | 7150 | Index | 161.278 | 14.941 | 147.000 | 192.000 |
| **Fuel** | 7150 | Index | 283.924 | 61.819 | 218.000 | 426.000 |
| **Business Services** | 7150 | Index | 143.923 | 6.156 | 136.000 | 157.000 |
| **Potato Farm Price** | 7150 | $ / lb. | 0.076 | 0.028 | 0.050 | 0.182 |

Notes: Retail sales data represent aggregate scanner data from Atlanta, Chicago, Dallas, Los Angeles and New York for the time period Jan. 8, 2006 through Sept. 28, 2008.

**Table 1b. Milk Summary Data**

| Variable | N | Units | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| **Brand 1 Share** | 104 | % | 25.172 | 11.811 | 0.815 | 53.250 |
| **Brand 2 Share** | 104 | % | 11.348 | 1.230 | 8.935 | 15.347 |
| **Brand 3 Share** | 104 | % | 10.733 | 4.772 | 0.527 | 22.835 |
| **Brand 4 Share** | 104 | % | 5.391 | 0.556 | 4.101 | 7.148 |
| **Brand 5 Share** | 104 | % | 4.164 | 2.510 | 0.924 | 14.971 |
| **Brand 6 Share** | 104 | % | 3.510 | 0.728 | 2.700 | 5.929 |
| **Brand 7 Share** | 104 | % | 2.579 | 1.801 | 0.652 | 6.898 |
| **Brand 8 Share** | 104 | % | 2.249 | 1.649 | 0.708 | 6.689 |
| **Brand 9 Share** | 104 | % | 1.826 | 0.360 | 1.378 | 2.755 |
| **Brand 10 Share** | 104 | % | 1.796 | 1.104 | 0.531 | 4.850 |
| **Brand 1 Price** | 104 | $ / oz | 0.028 | 0.003 | 0.020 | 0.033 |
| **Brand 2 Price** | 104 | $ / oz | 0.028 | 0.003 | 0.020 | 0.033 |
| **Brand 3 Price** | 104 | $ / oz | 0.034 | 0.003 | 0.025 | 0.038 |
| **Brand 4 price** | 104 | $ / oz | 0.034 | 0.003 | 0.024 | 0.038 |
| **Brand 5 Price** | 104 | $ / oz | 0.033 | 0.003 | 0.023 | 0.037 |
| **Brand 6 Price** | 104 | $ / oz | 0.029 | 0.003 | 0.018 | 0.033 |
| **Brand 7 Price** | 104 | $ / oz | 0.035 | 0.002 | 0.031 | 0.039 |
| **Brand 8 Price** | 104 | $ / oz | 0.029 | 0.003 | 0.020 | 0.034 |
| **Brand 9 Price** | 104 | $ / oz | 0.057 | 0.001 | 0.052 | 0.058 |
| **Brand 10 Price** | 104 | $ / oz | 0.035 | 0.002 | 0.031 | 0.039 |
| **Fat Content** | 104 | % | 1.144 | 0.811 | 0.000 | 0.200 |
| **Private Label** | 104 | % | 0.472 | 0.499 | 0.000 | 1.000 |
| **Organic** | 104 | % | 0.111 | 0.314 | 0.000 | 1.000 |
| **Education** | 18720 | Years | 10.603 | 0.407 | 10.084 | 11.220 |
| **Age** | 18720 | Years | 36.745 | 2.220 | 33.388 | 40.436 |
| **Grocery Wages** | 18720 | $ / Week | 339.803 | 5.591 | 329.700 | 353.680 |
| **Management Wages** | 18720 | $ / Week | 802.616 | 7.263 | 735.110 | 851.880 |
| **Electricity** | 18720 | Index | 170.938 | 5.645 | 163.200 | 181.600 |
| **Packaging** | 18720 | Index | 204.616 | 7.168 | 196.700 | 216.600 |
| **Fuel** | 18720 | Index | 277.683 | 71.538 | 159.600 | 422.600 |
| **Business Services** | 18720 | Index | 105.544 | 0.554 | 104.900 | 106.300 |
| **Milk Farm Price** | 18720 | $ / lb. | 0.194 | 0.027 | 0.145 | 0.219 |

Notes: Retail sales data represent scanner data from top ten brands chosen from market 1 over the time period March 4, 2007 through Feb. 22, 2009. Identity of markets and brands is not disclosed as per a confidentiality agreement with the data vendor.

**Table 2. Random Coefficient Nested Logit Demand Estimates: Potatoes**

| | Non-Random Parameter Model | | Random Parameter Model | |
|---|---|---|---|---|
| | Estimate | t-ratio | Estimate | t-ratio |
| **Discount** | 0.095* | 5.195 | 0.092* | 3.292 |
| **Discount*Price** | -0.032* | -2.194 | -0.031 | -1.554 |
| **Atlanta, GA** | -0.749* | -71.559 | -0.751* | -106.724 |
| **Chicago, IL** | -0.704* | -67.492 | -0.706* | -115.973 |
| **Dallas, TX** | -0.051* | -4.868 | -0.053* | -9.014 |
| **Los Angeles, CA** | 0.263* | 24.978 | 0.262* | 25.805 |
| **Fingerling** | -0.065* | -3.345 | -0.064 | -0.753 |
| **Idaho** | 0.144* | 6.905 | 0.142 | 1.702 |
| **Other** | 0.024 | 1.477 | 0.024 | 0.293 |
| **Purple** | -0.162* | -7.097 | -0.162 | -1.895 |
| **Red** | 0.133* | 6.625 | 0.132 | 0.972 |
| **Red Creamer** | 0.072* | 4.368 | 0.071 | 0.614 |
| **Russet** | 0.187* | 7.633 | 0.185 | 1.358 |
| **White** | 0.102* | 5.603 | 0.099 | 0.893 |
| **Yellow** | 0.097* | 5.507 | 0.095 | 0.604 |
| **Quarter 1** | -0.126* | -12.826 | -0.121* | -26.423 |
| **Quarter 2** | -0.289* | -29.293 | -0.291* | -65.126 |
| **Quarter 3** | -0.351* | -35.479 | -0.348* | -82.047 |
| **σ** | 0.954* | 201.021 | 0.958* | 169.968 |
| **Price and Intercept Parameters** | | | | |
| **Price** | -0.016* | -2.544 | -0.026* | -1.735 |
| **Constant** | -0.596* | -22.237 | -0.608* | -7.242 |
| **Standard Deviations of Random Parameters** | | | | |
| **Price** | N.A. | N.A. | 0.013* | 8.948 |
| **Constant** | N.A. | N.A. | 0.088* | 43.466 |
| **Random Parameter Functions** | | | | |
| **Price(Age)** | N.A. | N.A. | 0.004* | 7.264 |
| **Price(Education)** | N.A. | N.A. | -0.009* | -8.767 |
| **Constant(Age)** | N.A. | N.A. | -0.011* | -13.733 |
| **Constant(Education)** | N.A. | N.A. | N.A. | 28.154 |
| **LLF** | -897.127 | | 272.221 | |
| **Chi-square** | -16,826.913 | | 544.443 | |

[1] A single asterisk indicates significance at a 5.0% level. The chi-square statistic is twice the difference between the simulated likelihood value and the likelihood of a null model (all parameters restricted to zero).

**Table 3. Retail Potato Demand Elasticities: Top 10 Varieties, Average over all Markets**

| | Fingerling | Idaho | Other | Purple | Red | Red Creamer | Russet | White | Yell |
|---|---|---|---|---|---|---|---|---|---|
| **Fingerling** | -1.674 | 0.035 | 0.007 | 0.001 | 0.033 | 0.012 | 0.085 | 0.018 | 0. |
| **Idaho** | 0.035 | -0.314 | 0.041 | 0.035 | 0.067 | 0.046 | 0.118 | 0.052 | 0. |
| **Other** | 0.007 | 0.041 | -1.415 | 0.006 | 0.038 | 0.018 | 0.090 | 0.024 | 0. |
| **Purple** | 0.001 | 0.035 | 0.006 | -1.304 | 0.032 | 0.012 | 0.084 | 0.017 | 0. |
| **Red** | 0.033 | 0.067 | 0.038 | 0.032 | -0.430 | 0.044 | 0.116 | 0.049 | 0. |
| **Red Creamer** | 0.012 | 0.046 | 0.018 | 0.012 | 0.044 | -0.996 | 0.095 | 0.029 | 0. |
| **Russet** | 0.085 | 0.118 | 0.090 | 0.084 | 0.116 | 0.095 | -0.200 | 0.101 | 0. |
| **White** | 0.018 | 0.052 | 0.024 | 0.017 | 0.049 | 0.029 | 0.101 | -0.438 | 0. |
| **Yellow** | 0.018 | 0.052 | 0.023 | 0.017 | 0.049 | 0.028 | 0.101 | 0.034 | -0. |
| **Organic** | 0.003 | 0.037 | 0.009 | 0.003 | 0.034 | 0.014 | 0.086 | 0.020 | 0. |

Notes: Elasticities are averages for the top 10 varieties over all five markets. Entries in the table are defined as the elasticity of the row va
a change in the price of the column variety.

Table 4. Random Coefficient Nested Logit Demand Model: Milk

| Variable | Non-Random Parameter Model Estimate | t-ratio | Random Parameter Model Estimate | t-ratio |
|---|---|---|---|---|
| **Discount** | 0.000 | 0.021 | 0.002 | 0.836 |
| **Discount*Price** | -0.050 | -0.474 | -0.048 | -0.689 |
| **Trend** | 0.000* | 24.937 | 0.000* | 80.574 |
| **Atlanta, GA** | -0.028* | -12.937 | -0.033* | -25.514 |
| **Boston, MA** | 0.329* | 141.369 | 0.315* | 258.638 |
| **Dallas, TX** | -0.116* | -52.765 | -0.132* | -102.821 |
| **Denver, CO** | -0.134* | -60.719 | -0.134* | -106.055 |
| **Los Angeles, CA** | 1.666* | 732.543 | 1.631* | 1438.160 |
| **Minneapolis, MN** | -0.062* | -26.410 | -0.070* | -59.060 |
| **New York, NY** | 0.883* | 359.939 | 0.855* | 718.125 |
| **Phoenix, AZ** | 0.552* | 245.570 | 0.533* | 430.821 |
| **San Francisco, CA** | 0.308* | 136.427 | 0.293* | 224.942 |
| **σ** | 0.998* | 1515.852 | 0.998* | 1826.743 |
| **Price and Intercept Parameters** | | | | |
| **Price** | -0.112 | -1.582 | -0.653* | -11.045 |
| **Constant\|** | -2.374* | -735.321 | -2.365* | -618.538 |
| **Fat Content** | 0.000 | 0.576 | 0.002 | 1.169 |
| **Binary Private Label** | 0.001 | 0.596 | 0.006* | 3.328 |
| **Binary Organic\|** | 0.000 | -0.005 | 0.015* | 6.661 |
| **Standard Deviations of Random Parameters** | | | | |
| **Price** | N.A. | N.A. | 0.426* | 84.167 |
| **Constant\|** | N.A. | N.A. | 0.002* | 8.037 |
| **Fat Content** | N.A. | N.A. | 0.003* | 14.322 |
| **Binary Private Label** | N.A. | N.A. | 0.007* | 23.822 |
| **Binary Organic** | N.A. | N.A. | 0.004* | 4.988 |
| **Random Parameter Functions** | | | | |
| **Price (Education)** | N.A. | N.A. | -0.012* | -3.197 |
| **Price (Age)** | N.A. | N.A. | 0.014 | 1.820 |
| **Constant (Education)** | N.A. | N.A. | 0.000 | 0.782 |
| **Constant (Age)** | N.A. | N.A. | 0.001* | 2.959 |
| **Fat Content (Education)** | N.A. | N.A. | 0.000 | -0.366 |
| **Fat Content (Age)** | N.A. | N.A. | 0.000 | -0.950 |
| **Bi. Private Label (Edu.)** | N.A. | N.A. | 0.000* | -0.095 |
| **Bi. Private Label (Age)** | N.A. | N.A. | -0.001* | -2.861 |
| **Binary Organic (Edu.)** | N.A. | N.A. | 0.000* | -2.194 |

| | | | | |
|---|---|---|---|---|
| **Binary Organic (Age)** | N.A. | N.A. | 0.002* | -3.690 |
| **LLF** | 24,218.36 | | 30,547.03 | |
| **Chi-square** | 48,536.72 | | 61,094.06 | |

[1] Interaction variables of education and age with fat content, private label, and the Organic variable are not shown. A single asterisk indicates significance at a 5.0% level. The Chi-square statistic compares the LLF of the estimated model to a null model with all non-constant parameters restricted to zero.

**Table 5. Retail Milk Demand Elasticities: Market 1, Top 10 Brands**

| | Brand 1 | Brand 2 | Brand 3 | Brand 4 | Brand 5 | Brand 6 | Brand 7 | Brand 8 | Brand 9 | Brand 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Brand 1** | -2.786 | 0.760 | 0.646 | 0.615 | 0.611 | 0.603 | 0.861 | 0.865 | 0.570 | 0.842 |
| **Brand 2** | 0.760 | -3.119 | 0.393 | 0.276 | 0.236 | 0.222 | 0.408 | 0.418 | 0.206 | 0.368 |
| **Brand 3** | 0.646 | 0.393 | -3.271 | 0.313 | 0.290 | 0.282 | 0.393 | 0.398 | 0.268 | 0.375 |
| **Brand 4** | 0.615 | 0.276 | 0.313 | -4.890 | 0.167 | 0.157 | 0.233 | 0.239 | 0.149 | 0.207 |
| **Brand 5** | 0.611 | 0.236 | 0.290 | 0.167 | -4.878 | 0.113 | 0.169 | 0.176 | 0.108 | 0.140 |
| **Brand 6** | 0.603 | 0.222 | 0.282 | 0.157 | 0.113 | -4.604 | 0.149 | 0.156 | 0.098 | 0.120 |
| **Brand 7** | 0.861 | 0.408 | 0.393 | 0.233 | 0.169 | 0.149 | -3.160 | 0.459 | 0.137 | 0.332 |
| **Brand 8** | 0.865 | 0.418 | 0.398 | 0.239 | 0.176 | 0.156 | 0.459 | -3.827 | 0.143 | 0.357 |
| **Brand 9** | 0.570 | 0.206 | 0.268 | 0.149 | 0.108 | 0.098 | 0.137 | 0.143 | -5.118 | 0.111 |
| **Brand 10** | 0.842 | 0.368 | 0.375 | 0.207 | 0.140 | 0.120 | 0.332 | 0.357 | 0.111 | -4.082 |

Notes: Model includes 18 brands per market, with brands differing by market. Top 10 brands for the first market are shown for presentation purposes only. Elasticities for the remaining brands and markets are available from the authors. Entries in the table are defined as the elasticity of the row brand with respect to a change in the price of the column brand.

**Table 6. Retail and Wholesale Margin Model Estimates: Potato, GMM**

| | Vertical Model | | Retailer Only Model | |
|---|---|---|---|---|
| | **Estimate** | **t-ratio** | **Estimate** | **t-ratio** |
| **Wholesale Inputs** | | | | |
| **Packaging Cost** | 13.627* | 3.577 | N.A. | N.A. |
| **Fuel Cost** | 1.240* | 2.203 | N.A. | N.A. |
| **Business Services** | -40.931* | -4.751 | N.A. | N.A. |
| **Retail Inputs** | | | | |
| **Grocery Wages** | 9.507* | 5.161 | 7.381* | 2.447 |
| **Management Wages** | -1.313* | -5.995 | -0.516 | -1.043 |
| **Electricity Cost** | -1.056* | -5.617 | -1.110 | -1.659 |
| **Farm Price** | 0.678* | 8.103 | N.A. | N.A. |
| $\theta_0$ | 0.308* | 3.481 | N.A. | N.A. |
| $\theta_1$ | -0.215* | -9.770 | N.A. | N.A. |
| $\theta_2$ | -0.170* | -11.017 | N.A. | N.A. |
| $\varphi_0$ | 0.840* | 13.283 | 0.004* | 1.813 |
| $\varphi_1$ | -0.037 | 0.254 | 0.227* | 0.765 |
| $\varphi_2$ | -0.510* | 2.026 | -0.259 | -0.459 |
| **Finglerling** | 3.893* | 4.635 | 1.955* | 1.900 |
| **Idaho** | 1.762* | 2.099 | -1.383* | -1.368 |
| **Other** | 3.830* | 4.399 | 0.180* | 0.177 |
| **Purple** | 3.219* | 3.829 | 0.109* | 0.108 |
| **Red** | 1.945* | 2.316 | -1.202* | -1.189 |
| **Red Creamer** | 2.418* | 2.873 | -0.597* | -0.586 |
| **Russet** | 1.723* | 2.051 | -1.425* | -1.410 |
| **White** | 1.929* | 2.296 | -1.243* | -1.229 |
| **Yellow** | 2.108* | 2.510 | -1.033* | -1.022 |
| **Organic** | 2.180* | 2.589 | -2.289* | -2.269 |
| $\hat{\theta}$ | 0.248 | | N.A. | |
| $\hat{\varphi}$ | 0.828 | | 0.162 | |
| **GMM** | 271.135 | | 38.101 | |
| **Chi-Square** | 7,475.713 | | 40,460.761 | |

[1] A single asterisk indicates significance at a 5.0% level. Instruments for markup terms include interactions between input prices and variety-specific dummies, and lagged values of market share variables, promotion indicators and conditional shares. $\theta_j$ are components of the wholesale markup function (intercept, falling, rising wholesale prices, respectively) and $\varphi_j$ parameters are components of the retail markup function.

**Table 7. Retail and Wholesale Margin Model Estimates: Milk, GMM**

| | Vertical Model | | Retailer Only Model | |
|---|---|---|---|---|
| | Estimate | t-ratio | Estimate | t-ratio |
| **Wholesale Inputs** | | | | |
| **Packaging Cost** | -0.004* | -12.129 | N.A. | N.A. |
| **Fuel Cost** | -34.013* | -21.973 | N.A. | N.A. |
| **Business Services** | 0.720* | 22.727 | N.A. | N.A. |
| **Retail Inputs** | | | | |
| **Grocery Wages** | -3.348* | -15.514 | -0.467 | -38.198 |
| **Management Wages** | 40.428* | 18.816 | 2.111* | 52.729 |
| **Electricity Cost** | 12.954* | 11.545 | -3.809* | -48.593 |
| **Farm Price** | 0.066* | 6.727 | N.A. | N.A. |
| $\theta_0$ | 0.586* | 30.853 | N.A. | N.A. |
| $\theta_1$ | -1.181* | -11.538 | N.A. | N.A. |
| $\theta_2$ | 0.244* | 3.267 | N.A. | N.A. |
| $\varphi_0$ | 0.064* | 10.928 | 0.067* | 18.957 |
| $\varphi_1$ | -0.138* | -6.223 | 0.053* | 22.052 |
| $\varphi_2$ | 0.091* | 6.406 | -0.082* | -44.375 |
| **Atlanta, GA** | -1.007* | -9.251 | 0.319* | 67.135 |
| **Boston, MA** | -1.014* | -9.323 | 0.310* | 65.637 |
| **Dallas, TX** | -1.014* | -9.320 | 0.316* | 66.558 |
| **Denver, CO** | -1.017* | -9.347 | 0.308* | 65.061 |
| **Los Angeles, CA** | -1.073* | -9.906 | 0.343* | 67.935 |
| **Minneapolis, MN** | -1.015* | -9.327 | 0.302* | 64.022 |
| **New York, NY** | -1.004* | -9.224 | 0.321* | 67.693 |
| **Phoenix, AZ** | -1.042* | -9.584 | 0.335* | 68.178 |
| **San Francisco, CA** | -1.012* | -9.302 | 0.317* | 66.751 |
| **Seattle, WA** | -1.028* | -9.455 | 0.323* | 66.993 |
| $\hat{\theta}$ | 0.542 | | N.A. | |
| $\hat{\varphi}$ | 0.289 | | 0.028 | |
| **GMM** | 89.436 | | 2,793.957 | |
| **Chi-Square** | 4,889.241 | | 2,005.848 | |

[1] A single asterisk indicates significance at a 5.0% level. Instruments for markup terms include interactions between input prices and market-specific dummies, and lagged values of market share variables, promotion indicators and conditional shares. The $\theta_j$ parameters are components of the wholesale markup function (intercept, falling wholesale prices, and rising wholesale prices, respectively) and $\varphi_j$ parameters are components of the retail markup function.

**Table 8. Pass-Through of Commodity Price Inflation to Retail Prices, %**

| | | Potato | | | Milk | | |
|---|---|---|---|---|---|---|---|
| | | **Estimated (B.-Nash)** | **$\varphi = \theta = 0$ (Comp)** | **$\varphi = \theta = 1$ (Monopoly)** | **Estimated (B.-Nash)** | **$\varphi = \theta = 0$ (Comp)** | **$\varphi = \theta = 1$ (Monopoly)** |
| | $p_j^0$ | $0.778 | $0.778 | $0.778 | $0.101 | $0.101 | $0.101 |
| **Rising**[1] | $p_j^1$ | $0.846 | $0.845 | $0.815 | $0.105 | $0.108 | $0.110 |
| | $\Delta_{RF}$ | 67.48% | 67.83% | 37.01% | 4.49% | 6.56% | 8.85% |
| | $p_j^0$ | $0.778 | $0.778 | $0.778 | $0.101 | $0.101 | $0.101 |
| **Falling** | $p_j^1$ | $0.698 | $0.710 | $0.741 | $0.095 | $0.095 | $0.097 |
| | $\Delta_{RF}$ | 79.54% | 67.83% | 37.02% | 6.10% | 6.56% | 4.27% |

[1] In this table, $\Delta_{RF}$ is the pass-through rate between commodity and retail prices, $p_j^0$ is the initial fitted retail price (before commodity price increase), and $p_j^1$ is the new equilibrium price.